International Journal of Engineering Research And Management (IJERM)
ISSN: 2349- 2058, Volume-12, Issue-09, September 2025

Risk Assessment of Road Transportation of Hazardous Chemical Tank Trucks Based On Fuzzy DBN

Li Zhiqiang, Shi Jianyun

***Abstract*— The "Identification of Major Hazard Sources for Hazardous Chemicals" establishes regulations for production, storage, use, and trading of hazardous chemicals. However, it lacks provisions for transportation – a mobile hazard source requiring specialized attention. As China's primary mode of hazardous chemical transport remains road transportation, which offers flexibility, cost-effectiveness, and efficiency, the challenges persist. Given the inherent risks of flammability, explosiveness, and corrosiveness, coupled with unpredictable factors during transit (particularly in tankers where uncertainties are most pronounced), accidents involving hazardous chemical tankers can have catastrophic consequences. To minimize accident rates, conducting risk assessments for road transport is crucial. This study employs Bayesian networks derived from junction graphs, integrates triangular fuzzy theory, and applies expert-weighted similarity aggregation to synthesize expert opinions. Through posterior probability analysis, sensitivity testing, and importance evaluation, key factors contributing to tank ruptures are identified. The developed dynamic risk assessment model for road transport of hazardous chemical tankers utilizes GeNle software to address uncertain risk factors.**

***Index Terms*— risk assessment; triangular fuzzy theory; similarity aggregation method; Bayesian network**

LDA-BN MODEL THEORY

LDA principle and analysis process

To effectively uncover thematic structures in texts, this study employs the Latent Dirichlet Allocation (LDA) model. By modeling latent semantic distributions within documents, LDA identifies commonalities in accident descriptions. As a three-level Bayesian probabilistic generative model, LDA fundamentally treats documents as topic probability mixtures where topics represent θ θ word probability distributions. The ϕ model ϕ operates through two key steps: First, assigning a topic distribution (T) to each document and defining a word distribution (W) for each topic, both following Dirichlet prior distributions. Second, for each word, the system first samples a topic from the document's topic distribution, then selects a word from that topic's distribution. Through repeated sampling across large-scale texts, the model continuously stabilizes the probabilistic relationships between topics and keywords, thereby achieving the goal of extracting implicit semantic structures.

Manuscript received September 27, 2025
Li Zhiqiang, Dalian Jiaotong University, Dalian, China
Shi Jianyun, Dalian Jiaotong University, Dalian, China

BN model principle

Bayesian network (BN) is a kind of probabilistic graph model defined by a $G=(V,E)$ directed acyclic graph and conditional probability distribution. Its joint probability distribution can be decomposed as:

$$P(X_1,X_2,\ldots,X_n)=\prod_{i=1}^{n} P(X_i \mid Pa(X_i))\#(1)$$

It represents $X_i Pa(X_i) G$ a random variable, which is the set of its parent nodes. Structural learning aims to determine the topology of graphs. Common methods include: constraint-based approaches based on independence tests (such as the PC algorithm), search methods based on scoring functions (such as BIC and BDe scoring), and hybrid methods combining both approaches.

Parameter learning is used to estimate $P(X_i \square Pa(X_i))$ the conditional probability distribution. When the data is complete, it can be directly calculated by maximum likelihood estimation (MLE):

$$\hat{\theta}_{x_i|pa_i}=\frac{N(x_i,pa_i)}{N(pa_i)}\#(2)$$

Where $N(x_i,pa_i)(X_i=x_i,Pa(X_i)=pa_i)$ represents the frequency of simultaneous occurrence of events in the observation. When there are missing values or hidden variables, the expectation-maximization (EM) algorithm is often used to iteratively optimize the likelihood function.This study proposes a risk assessment method for transportation of hazardous chemical tank trucks by integrating LDA topic model and Bayesian network.

Accident data processing and risk identification

In order to ensure the accuracy and practicability of theme extraction, this paper designs a preprocessing process in the data processing stage, including text cleaning, professional dictionary construction, Chinese word segmentation, text vectorization, LDA modeling and semantic classification.

In text cleaning, we developed a lexicon containing stop words such as pauses, quantifiers, conjunctions, subjects, common verbs, synonyms, and other non-core terms. To enhance coverage in professional semantic recognition, we created a specialized dictionary for hazardous chemical tanker transportation by integrating terminology usage conventions and regulatory standards from the dangerous goods transport sector, as shown in Table.

Special dictionary for transportation of hazardous chemical tank trucks

class	Example of a technical term
Hazard types	LPG, chlorine, methanol, benzene, diesel, natural gas, acrylonitrile, ammonia, nitric acid, styrene
vehicle type	Tanker, tank car, tractor, semi-trailer, van, container truck, special transport vehicle
Contingency response	Blockade, evacuation, fire fighting, dilution, cooling, drainage, alert, isolation, leak sealing, transfer, monitoring
Type of accident	Leakage, explosion, combustion, collision, rollover, rear-end collision, scraping, fire, poisoning, corrosion
Vehicles	Valves, flanges, pipes, tanks, breather valves, level gauges, pressure gauges, emergency shut-off devices, heaters
Type of road	Highway, national road, provincial road, township road, tunnel, bridge, ramp, toll station, service area, roundabout
weather regime	Rainy, snowy, foggy, thunderstorms, strong winds, icing, low visibility
Personnel conduct	Fatigue driving, drunk driving, driving without a license, operating without authorization, speeding, improper operation, playing with your phone, smoking

After word segmentation, we constructed a bag-of-words model and performed text vectorization. Using the CountVectorizer, we counted the occurrences of each word across different texts to generate a document-word matrix. The matrix was then normalized to enable high-dimensional representation of texts in a word vector space.

The optimal number of topics significantly determines LDA model performance. To ensure both model adaptability and semantic clarity, this study combines Perplexity evaluation with a Coherence Score metric for comprehensive validation. Perplexity measures a model's ability to predict unseen text, with lower values indicating stronger generalization. The Coherence Score assesses semantic coherence within topics, where higher scores indicate greater semantic cohesion and clarity. By testing topic counts from K=2 to 10, we calculated corresponding Perplexity and Coherence Scores before finalizing the optimal topic count of 5.

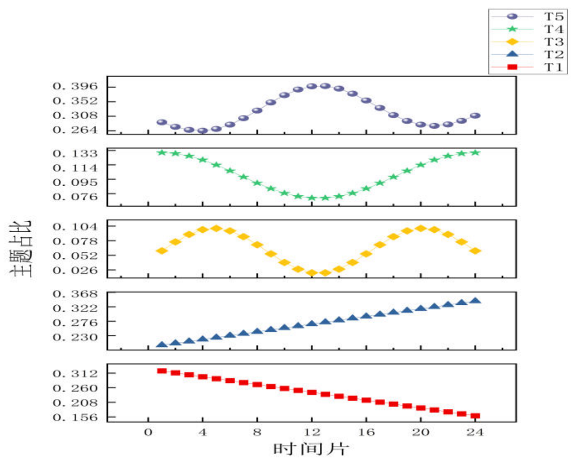
In the actual modeling process, this paper first divides the collected accident texts into several equally-length time windows. The quarterly time window setting achieves a good balance between corpus density and semantic stability, dividing the period from 2018 to 2023 into 24 time segments. Topic models are trained on each time segment, with the prior topics from the previous segment serving as the initial distribution for the current segment to ensure continuous topic evolution. To maintain modeling stability and comparability, the number of topics K in dynamic LDA remains set at 5, consistent with static models. The model training employs variational Bayesian inference algorithm implemented within Gensim framework. To minimize training fluctuations, a maximum iteration count of 100 is set with a convergence threshold of 0.001. Additionally, to enhance semantic interpretability, the top 10 keywords for each topic in model outputs are retained and manually categorized using tagging methods. The training results are summarized in the table below, listing high-frequency keywords under each topic category.

Topic extraction results from hazardous tank truck accident texts

Theme name	High frequency keywords
Driving behavior and operational errors	Speeding, tired driving, distracted driving, illegal parking, failure to keep a safe distance, human error and so on
Vehicle technical status and equipment failure	Brake failure, tire abnormality, suspension abnormality, tank corrosion, safety valve failure
Environmental and road conditions	Road design defects, strong side wind, low visibility, rain and snow weather, slippery road
Transport management and system implementation	Improper GPS monitoring, failure to check the condition of vehicles regularly, lack of safety education, lack of system, inadequate training
Accident consequences and emergency response	Leakage, fire, explosion, poisoning, environmental pollution, ignition source, emergency evacuation

Based on the five major themes and their high-frequency keywords extracted from the table, the chart below illustrates the relative weight trends of each theme across 24 time windows. The T1 theme (Driving Behavior and Operational Errors) encompasses terms such as "speeding", "fatigued driving", and "failure to maintain safe distance".

The proportion in the first quarter of 2018 was 0.32, and decreased to 0.16 in the fourth quarter of 2023, indicating that the proportion of this kind of factors in the text expression is significantly weakened, reflecting that with the strengthening of road law enforcement and the improvement of driver management level in recent years, the relevant risks have been effectively contained.



Relative weight change trend of each theme in 24 time windows

In contrast, the T3 (Environmental and Road Conditions) theme has seen a steady increase in prominence, rising from 0.20 to 0.34. Keywords such as "low visibility," "strong crosswinds," "slippery roads," and "rain/snow weather" highlight how extreme weather events and complex road conditions have become focal points of public and industry concern, likely linked to macro factors like climate change and infrastructure delays. The T2 (Vehicle Technical Status and Equipment Failures) theme shows significant intensification during 2020-2021, with keywords including "tank corrosion," "safety valve failure," and "tire abnormalities" peaking in prominence. This surge coincides with a concentrated exposure period for equipment aging and maintenance deficiencies in real-world operations. Subsequently, its proportion stabilized, indicating periodic fluctuations in public attention toward equipment safety risks.

The T4 theme (Transportation Management and System Implementation) covers expressions such as "improper GPS monitoring", "lack of training", and "inadequate regulations". Over time, its proportion has remained relatively stable with minor fluctuations, indicating that inadequate management system implementation continues to be a significant hidden risk factor. Finally, the T5 theme (Accident Consequences and Emergency Response) primarily includes descriptions like "leakage", "fire", "explosion", and "emergency evacuation". Its overall proportion has shown a slight increase, reflecting growing public concern regarding accident damage control capabilities and emergency response efficiency.

As shown in the thematic distribution similarity curves of adjacent time slices in the figure, the average semantic similarity of all five themes across consecutive quarters remained above 0.80, with T3 and T5 themes demonstrating particularly pronounced semantic clustering tendencies. This indicates that the Dynamic Latent Dirichlet Allocation (LDA) model not only effectively captures temporal continuity and transition patterns in thematic semantics, but also exhibits strong structural stability and temporal robustness.

BN MODEL CONSTRUCTION

Based on risk identification of road transportation processes involving hazardous chemical tankers and collected accident data, this study conducts risk assessments for tanker transport accidents caused by container ruptures, including subsequent leaks leading to fires and explosions. After screening evaluation indicators through expert consultation, the results are visualized using a diamond diagram (see Table). The diagram employs X (base event), G (intermediate event), T (top event), SB (safety barrier), and R (accident outcome) as key components.

Node number	Node name	Node number	Node name	Node number	Node name
X1	furious driving	X15	high temperature weather	Y3	External environmental factors
X2	fatigue driving	X16	overload	Y4	management factors
X3	Distracted driving	X17	Transport route is not reasonable	G1	Vehicle rollover/collision
X4	illegal parking	X18	GPS monitoring is not properly done	G2	Vessel/equipment defects
X5	Illegal braking	X19	Failure to check the condition of the vehicle regularly	SB1	incendiary source
X6	Failure to maintain safe distance	X20	Lack of safety education	SB2	Reach the explosion limit
X7	braking failure	X21	Illegal transport	SB3	High concentration area personnel exposure
X8	Turning failure	X22	Welding defects	SB4	Emergency evacuation is not timely
X9	Tire irregularities	X23	Flange seal failure	A1	let out
X10	Hanging exception	X24	Deflection plate failure	A2	Vehicle damage
X11	Road conditions are bad	X25	Tank corrosion	A3	fire
X12	Road design defects	X26	Safety valve failure	A4	explode
X13	Strong side wind	Y1	Driver factors	A5	Poisoning/Asphyxiation
X14	Low visibility	Y2	Vehicles factor	A6	environmental pollution

DETERMINATION AND CALCULATION OF PRIOR PROBABILITY

Regarding tank factors, vehicle factors, and environmental factors, the prior probability of these three evaluation indicators can be referenced from the occurrence probabilities of historical accident data collected. The frequency of accidents caused by these factors serves as the prior probability for corresponding root nodes. For driver factors and management factors characterized by variability, complexity, and time-sensitive uncertainties, we introduce triangular fuzzy numbers from fuzzy set theory first proposed by Zadeh in 1965. Through expert scoring and a similarity aggregation method considering expert weights, the resulting fuzzy possibility values (FPS) are used as prior probabilities for corresponding root nodes. Four experts were invited to score six indicators according to the scoring criteria outlined in Table 2, with expert weights calculated based on Table 3. The expert weight set ranges from [0.3, 0.4, 0.1, 0.2]. Referring to the improved similarity aggregation method mentioned in Reference [4], the steps are as follows:

1) *Determine expert w_i weights*

Educational background, experience, professional title and achievements are taken $i c$ as the scoring criteria and divided into four levels respectively. The corresponding score of each expert is calculated, and then the four experts are normalized to obtain the weight set of experts.

$$w_i=\frac{C_i}{\sum_{i=1}^{n} C_i}\#(3)$$

In the $C_i i n w_i$ formula, is the score value of the nth expert, is the number of experts, and is the weight of the expert.

2) *Determine the consistency $S(\tilde{A},\tilde{B})$ between expert opinions*

The triangular fuzzy number is used as the membership degree function

$$\mu\tilde{A}_{(x)}=\begin{cases}0 & x\leq a,\ x>C\\ \dfrac{x-a}{b-a} & a<x\leq b\\ \dfrac{c-x}{c-b} & b<x\leq c\end{cases}\#(4)$$

In the form and a, b, $c\in R a<b<c$

According to Table 2, the risk degree determined by experts is converted into triangular fuzzy number.

$$s(\tilde{A}_i,\tilde{A}_j)=1-\frac{1}{3}\left(|a_i-a_j|+|b_i-b_j|+|c_i-c_j|\right)\#(5)$$

In the formula, are the triangular fuzzy numbers of the first expert respectively, $S(\tilde{A}_i,\tilde{A}_j)\epsilon[0,1]\tilde{A}_i\tilde{A}_j i j\tilde{A}_i=(a_i,b_i,C_i)\tilde{A}_j=(a_j,b_j,C_j)$

3) *Determine the weighted consistency W_{A_i} of expert opinions*

$$W_{Ai}=\frac{\sum_{j=1}^{n} W_j\cdot S(\tilde{A}_i,\tilde{A}_j)}{\sum_{j=1}^{n} W_j},i\neq j\#(6)$$

4) *Determine the relative consistency R_{Ai} of expert opinions*

$$R_{Ai}=\frac{W_{Ai}}{\sum_{i=1}^{g} W_{A_i}}\#(7)$$

5) *Determine the consistency coefficient C_{ci} of expert opinions*

$$C_{ci}=\beta\cdot W_i+(1-\beta)R_{Ai}\#(8)$$

In this $\beta\in[0,1]W_i W_{Ai}\beta$ formula, the relaxation factor is the key factor of balance and equilibrium, and the value of is taken as 0.5 according to reference [4].

6) *Determine the overall $\tilde{A}$ fuzzy number*

$$\tilde{A}=C_{c1}\cdot\tilde{A}_1+C_{C2}\cdot\tilde{A}_2+C_{cn}\cdot\tilde{A}_n\#(9)$$

7) Deblurring

The fuzzy possibility value (FPS) is obtained by defuzzification of triangular fuzzy number using the center of gravity method

$$FPS=\frac{\int_a^b \frac{x-a}{b-a}x\,dx+\int_b^c \frac{c-x}{c-b}x\,dx}{\int_a^b \frac{x-a}{b-a}\,dx+\int_b^c \frac{c-x}{c-b}\,dx}=\frac{1}{3}(a+b+c)\#(10)$$

Spectrum criteria table

degree of risk	The corresponding triangular fuzzy number
low	(0, 0.1, 0.3)
lower	(0.2, 0.3, 0.4)
centre	(0.3, 0.5, 0.6)
higher	(0.5, 0.7, 0.8)
tall	(0.7, 0.9, 1.0)

Expert weight determination table

metric	type	value	metric	type	value
record of formal schooling	doctor	4	professional ranks and titles	professor	4
	Master	3		adjunct professor	3
	undergraduate course	2		lecturer	2
	junior college	1		assistant	1
experience	> 20 years	4	achievement	> 30 pieces	4
	10-20 years	3		20-30 pieces	3
	5-10 years	2		10-20 pieces	2
	<5 years	1		<10	1

CONDITIONAL PROBABILITY CALCULATION

In traditional Bayesian network models, conditional probabilities are primarily derived from logical gate relationships in fault trees, with calculated probabilities represented by binary values (0 and 1). However, real-world road transport accidents involving hazardous chemical tankers involve complex $X_0 X_i \square X_{ot\square}$influencing factors, most of which result from multiple simultaneous causes. As referenced in [5], a missing probability model is employed where the missing node (denoted as) represents the root node of a specific node G, while other root nodes are collectively indicated. The formula for calculating conditional probabilities is as follows:

$$P(G|x_i)=1-(1-P_{Xot\square})(1-P_{x_i})=P_{X_i}+P_{Xot\square}-P_{X_i}P_{Xot\square}\#(11)$$

$$P(G|x_i)=P_{Xot\square}\#(12)$$

Equations (11) and (12) are combined to get

$$P_{x_i}=\frac{P(G|x_i)-P(G|\overline{x_i})}{1-p(G|\overline{x_i})}\#(13)$$

In the $\overline{x}_i X_0$formula, it represents that the event does not occur. According to Equation (13), the connection probability of all root nodes at this node can be calculated. Let the connection probability be 0.1, and the conditional probability of the node is

$$P(G=1)=1-(1-p_0)\Pi_{i\square Xot\square}(1-P_i)\#(14)$$

This paper holds that the combination of barrier nodes will inevitably lead to certain accident consequences. For example, the simultaneous occurrence of leakage and instantaneous ignition source will inevitably lead to fire accidents. As for the conditional probability of accident consequences, 0 and 1 are assigned according to the actual occurrence situation.

Posterior probability reasoning and sensitivity calculation

By inputting prior probabilities into Bayesian networks and obtaining posterior probabilities for each node, we can identify the primary factors contributing to accidents. As outlined in reference [6], the network sensitivity analysis $V_{RO}\,V_{RO}$employs the Ratio of Occurrence Variation (ROV) method to pinpoint critical root nodes affecting accident outcomes. The larger the node value (expressed as), the greater the corresponding factor's influence on accident occurrence. The calculation formula is

$$V_{R0}=\frac{P_b-P_f}{P_f}\#(15)$$

In the $P_b P_f$formula, represents the posterior probability of a node, and represents the prior probability of a node.

A. *Importance calculation*

1) *Probability importance*

By analyzing the conditional probabilities of tank rupture occurring in both root nodes and non-root nodes, this method calculates and prioritizes the probability importance of each root node. Specifically, reducing the occurrence probability of high-risk root nodes can effectively lower accident risks. In this study, all root nodes are categorized into two states, with their probability importance calculated using the following formula:

$$I_{pr}(x_i)=P_{YT}-P_{NT}\#(16)$$

In the $P_{YT}P_{NT}$formula, it represents the probability of tank rupture when the node occurs, and it represents the probability of tank rupture when the node does not occur.

2) *Key importance*

Critical importance identifies the key elements that lead to an accident. The critical importance formula for root nodes is

$$I_{cr}(x_i)=\frac{P_Y\square I_{P_r}(x_i)}{P_T}\#(17)$$

In the $P_Y P_T$formula, represents the probability of occurrence of the node, and represents the probability of tank rupture.

3) Risk importance

Risk importance helps identify key root nodes requiring prioritization in risk assessments, thereby reducing the likelihood of accidents. Both the probability importance of a node and its number of child and parent nodes significantly influence its overall risk significance. The formula for calculating root node risk importance is

$$I_{fv}(x_i)=\frac{P_T-P_{NT}}{P_T}\#(18)$$

The calculation results according to the above formula are shown in Table ,

name of index	**prior probability**	**posterior probability**	**ROV**	**Probability importance**	**Order of probability**	**Key importance**	**Critical sorting**	**Risk importance**	**Risk prioritization**
X1 Speeding	0.18	0.55	2.05	0.37	3	0.0666	5	0.76	3
X2 Fatigue driving	0.32	0.62	0.94	0.3	10	0.096	3	0.28	17
X3 Distracted driving	0.16	0.49	2.06	0.33	8	0.0528	10	0.68	4
X4 Illegal parking	0.21	0.48	1.29	0.27	15	0.0567	9	0.35	11
X5 Illegal braking	0.2	0.43	1.15	0.23	23	0.046	13	0.26	20
X6 did not maintain a safe distance	0.19	0.4	1.11	0.21	25	0.0399	16	0.23	23
X7 Brake failure	0.14	0.42	2	0.28	13	0.0392	17	0.56	8
X8 steering failure	0.15	0.39	1.6	0.24	22	0.036	18	0.38	10
X9 tire anomalies	0.18	0.44	1.44	0.26	17	0.0468	12	0.37	9
X10 Hanging exception	0.13	0.36	1.77	0.23	21	0.0299	20	0.41	12
X11 Road conditions are bad	0.12	0.32	1.67	0.2	27	0.024	24	0.33	14
X12 Road design defects	0.16	0.37	1.31	0.21	26	0.0336	19	0.28	18
X13 Strong crosswinds	0.14	0.31	1.21	0.17	28	0.0238	25	0.21	26
X14 Low visibility	0.13	0.29	1.23	0.16	30	0.0208	28	0.2	27
X15 High temperatures	0.17	0.36	1.12	0.19	29	0.0323	21	0.21	25
X16 Overloading	0.33	0.6	0.82	0.27	14	0.0891	4	0.22	24
X17 Transport route is not reasonable	0.26	0.53	1.03	0.27	12	0.0702	7	0.28	19
X18 GPS monitoring is not properly done	0.24	0.45	0.88	0.21	24	0.0504	11	0.19	28

X19 No regular inspection of vehicle condition	0.21	0.41	0.95	0.2	28	0.042	14	0.19	29
X20 Lack of safety education	0.25	0.49	0.96	0.24	20	0.06	8	0.23	22
X21 Illegal transport	0.3	0.57	0.9	0.27	11	0.081	6	0.24	21
X22 Welding defects	0.14	0.48	2.43	0.34	5	0.0476	15	0.83	2
X23 Flange seal failure	0.18	0.5	1.78	0.32	9	0.0576	9	0.57	7
X24 Wave guard plate failed	0.2	0.53	1.65	0.33	6	0.066	5	0.55	6
X25 Tank corrosion	0.15	0.55	2.67	0.4	1	0.06	8	1.07	1
X26 Safety valve failure	0.19	0.51	1.68	0.32	7	0.0608	7	0.54	5
SB1 ignition source	0.25	0.63	1.52	0.38	2	0.095	3	0.58	8
SB2 Explosive Limits	0.3	0.68	1.27	0.38	4	0.114	1	0.48	10
Exposure of SB3 personnel	0.12	0.47	2.92	0.35	4	0.042	14	1.02	2
SB4 Emergency evacuation is not timely	0.25	0.58	1.32	0.33	6	0.0825	2	0.44	11

Bayesian network analysis of tank truck transportation risks based on multi-source data coupling reveals that road transport accidents involving hazardous chemical tankers exhibit complex and highly coupled causes. When a leakage incident (A1) is predetermined to occur, both the posterior probabilities of driver operational errors and tank body defects show significant increases.The posterior probability of speeding reached 55%, while distracted driving accounted for 49% and overloaded transportation 60%, all showing significant relative increases (ROVs exceeding 0.8). These findings highlight the critical role of driver behavior in transport risks, aligning with existing research conclusions and actual accident reports. Structural defects such as tank corrosion and weld defects also significantly contribute to accidents, ranking high in probability importance. Analysis of barrier nodes—particularly human exposure and delayed emergency evacuation—revealed heightened sensitivity, amplifying consequence severity. The prioritization of probability and critical importance further demonstrates multi-factor coupling risks: speeding, tank corrosion, and overloaded transportation form high-risk combinations, while irrational transport routes and fatigued driving exhibit cumulative effects on accident probability, equally requiring attention. Risk assessment indicators indicate that enhancing driver safety awareness, strengthening safety education, improving tank and equipment inspection efficiency, and perfecting emergency response systems are key measures to reduce accident risks.

CONCLUSIONS

In this paper, five types of risk factors in road transportation of hazardous chemical tank trucks are identified by collecting relevant accident data and analyzing them over the past five years.

Based on the transformation of tie graph to Bayesian network, and the introduction of triangle fuzzy number in fuzzy set theory, a dynamic risk assessment model for road transportation of hazardous chemical tank trucks is constructed by expert scoring and similar aggregation method considering expert weight.

Using GeNle software, we constructed the model and analyzed the results. Through posterior probability reasoning, sensitivity analysis, and importance analysis, it was concluded that speeding, operational errors, brake failure, and factors related to the tank itself were key contributors to the tank rupture. Observations of probability changes in accident consequences revealed that when a tank ruptures, the risk of fire and explosion incidents increases significantly, particularly explosions.

REFERENCE

[1] Tao Jian. Risk assessment of dangerous goods transportation on mountain roads based on Bayesian network [D]. Chang 'an University, 2011.

[2] Yang Nengpu, Yang Yuefang, and Feng Wei. Risk Assessment of Railway Dangerous Goods Transportation Process Based on Fuzzy Bayesian Network [J]. Journal of Railway Science, 2014,36(07):8-15.

[3] Tang Yuan. Research on Safety Risk Assessment of Dangerous Goods Highway Transportation Based on BN-Bow-Tie Model [D]. Southwest Jiaotong University, 2024.DOI:10.27414/d.cnki.gxnju.2022.002538.

[4] Zhang Yexiang, Zhang Jiechao, Yang Youhong, et al. Research on Dynamic Safety Risk Evaluation of Highway Engineering Construction Based on Fuzzy Dynamic Bayesian Network [J/OL]. Henan Science, 1-7[2024-05-15].http://kns.cnki.net/kcms/detail/41.1084.N.20240407.1025.006.html.

[5] Zhang Yuanyuan, Zhang Chunchang, Sun Hu, et al. Risk Assessment of Methanol Tanker Refueling Between Ships Based on Dynamic Bayesian Networks [J/OL]. Journal of Shanghai Maritime University, 1-12[2024-05-15].https://doi.org/10.13340/j.jsmu.202308110177.

[6] Lu Lianghai, Liang Yiyuan, Zhang Haobin, et al. Research on Dynamic Risk Assessment Method for Indoor Gas Leakage in Fuzzy DBN Systems [J]. Journal of Safety and Environmental Science, 2024,24(04):1337-1345.DOI:10.13637/j.issn.1009-6094.2023.05.

[7] Cao Jian, Shi Shiliang, Lu Yi, et al. Analysis of Hazardous Chemicals Accidents in Tanker Road Transportation from 2013 to 2018 [J]. Journal of Safety Science of China, 2020,30(02):119-126.DOI:10.16265/j.cnki.issn1003-3033.2020.02.019.

[8] Wang Yonggang, Sun Yao. Application of BN-based FTA in General Aviation Risk Assessment [J]. Journal of Safety Science, China, 2010,20(03):19-23.DOI:10.16265/j.cnki.issn1003-3033.2010.03.017.

[9] Wu Xianguo, Ding Baojun, Zhang Limao, et al. Research on Subway Construction Risk Management Based on Bayesian Networks [J]. Journal of Safety Science in China, 2014,24(01):84-89.DOI:10.16265/j.cnki.issn1003-3033.2014.01.025.

[10] Li Xinhong, Zhu Hongwei, Chen Guoming, et al. A Bayesian dynamic model for risk analysis of submarine oil and gas pipeline leakage accidents [J]. Journal of Safety Science in China, 2015,25(04):75-80.DOI:10.16265/j.cnki.issn1003-3033.2015.04.013.

[11] Zhu Ting, Zhao Laijun, and Wang Xulei. Analysis of Road Transport Accidents Involving Hazardous Chemicals Based on Bayesian Networks [J]. Journal of Safety and Environmental Science, 2016,16(02):53-60.DOI:10.13637/j.issn.1009-6094.2016.02.011.

[12] Shao Bo, Liu Qiao, Ke Shangang, et al. Fusing LDA-BN for Causation Analysis of Ship Collision Accidents [J]. Journal of Safety and Environmental Science, 2025,25(01):157-164.DOI:10.13637/j.issn.1009-6094.2024.1136.

[13] Ren Yihua. Dynamic Risk Assessment of Road Transportation of Dangerous Goods [D]. Dalian Jiaotong University, 2024.DOI:10.26990/d.cnki.gsltc.2024.000389.

[14] Tao Jian. Risk assessment of dangerous goods transportation on mountain roads based on Bayesian network [D]. Chang 'an University, 2011.

[15] Yang Nengpu, Yang Yuefang, and Feng Wei. Risk Assessment of Railway Dangerous Goods Transportation Process Based on Fuzzy Bayesian Network [J]. Journal of Railway Science, 2014,36(07):8-15.

[16] Tang Yuan. Research on Safety Risk Assessment of Dangerous Goods Highway Transportation Based on BN-Bow-Tie Model [D]. Southwest Jiaotong University, 2024.DOI:10.27414/d.cnki.gxnju.2022.002538.